A Study of Chinese Private Passenger Cars Based on BP Neural Network

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***Abstract*—This study employs BP neural network to simulate the development of Chinese private passenger cars. Considering the uncertain and complex environment for the development of private passenger cars, indicators of economy, population, price, infrastructure, income, energy and some other fields which have major impacts on it are selected at first. The network is proved to be operable to simulate the progress of Chinese private passenger cars after modeling, training and generalization test. Based on the BP neural network model, sensitivity analysis of each indicator is carried on and shows that the sensitivity coefficients of fuel price change suddenly. This special phenomenon reveals that the development of Chinese private passenger cars may be seriously affected by the recent high fuel price. This finding is also consistent with facts and figures.**

Keywords-BP neural network; sensitivity analysis; private passenger cars; fuel price

I. INTRODUCTION

In china, according to the National Bureau of Statistics, there were only 240,000 private passenger cars in 1990. After the accession to the World Trade Organization, automobile market was opening up. Driven by the rapid development of the domestic automobile industry, the number of private passenger cars increased gradually. In recent years, he flourishing market of private passenger cars in China, which attracts all the society's attention, is not only a strong driving force of economic development, but also closely related to people's livelihood.

With the ever-changing social environment, the development of private passenger cars has even closer relations with economic development, price, infrastructure construction, income, and some other fields.

In view of the uncertain and complex environment, this paper selects BP neural network model to simulate the development of private passenger cars and uses sensitivity analysis to discuss how the selecting indicators affect on the development of the private passenger cars.

II. INDICATORS AND SAMPLES

The selection of indicators and samples, which should be solved at the beginning, is the interface of object and network model. Samples should accurately reflect the process of the private passenger cars, and besides, we should take into account of the performance of network model. Three steps are put forward as follows.

A. Selecting Indicators

In consideration of the practical experience of modeling, a large number of indicators were selected. After training on the various networks and comparing the experimental results, some indicators with a high degree of correlation were removed and the best indicators were selected out according to the results of training. Eventually we find six input indicators and one output indicator, shown in Tab. Ⅰ.

The selected indicators have covered main aspects that affect the development of private passenger cars. Moreover, we take full account of the current characteristics in China. For example, population indicator is total number of employed persons, which reflects the characteristics of purchasers, rather than simply total population. Income and price indicators, which are indices in urban area, embody the characteristics of private passenger cars' running scope.

TABLE I. SELECTING INDICATORS

Fields of Indicators	**Indicators**	
	Selected indicators	***Spare indicators***
W1 Economy	Gross Domestic Product (100 million yuan)	Per capita GDP (yuan/person)
W2 Population	Total number of employed persons (10 000 persons)	Total population of urban area (10 000 persons)
W3 Infrastructure	Length of highways （10000 km）	Length of expressway （10000 km）
W4 Income	Annual per capita disposable income index of urban residents	
W5 Price	Consumer price index of urban area	Consumer price index
W6 Energy	Purchasing price index of fuel and energy	Total energy consumption
A Output Indicator	Number of private-owned passenger cars (10 000 units)	

B. Selecting Original Samples

Select the data from China Statistical Yearbook 1993~2004 (12 years) as original samples, shown in Tab.Ⅱ.

TABLE II. ORIGINAL SAMPLES

Year	Samples of Indicators						
	W1	W2	W3	W4	W5	W6	A
1993	34634.4	66808	108.35	255.1	294.2	163.6	59.85
1994	46759.4	67455	111.78	276.8	367.8	193.4	78.62
1995	58478.1	68065	115.70	290.3	429.6	222.9	114.15
1996	67884.6	68950	118.58	301.6	467.4	231.6	143.04
1997	74462.6	69820	122.64	311.9	481.9	234.6	191.27
1998	78345.2	70637	127.85	329.9	479.0	224.7	230.65
1999	82067.5	71394	135.17	360.6	472.8	217.3	304.09
2000	89468.1	72085	140.27	383.7	476.6	228.4	365.09
2001	97314.8	73025	169.80	416.3	479.9	227.9	469.85
2002	105172.3	73740	176.52	472.1	475.1	222.7	623.76
2003	117390.2	74432	180.98	514.6	479.4	233.4	845.87
2004	136875.9	75200	187.07	554.2	495.2	260.0	1069.69

C. Standardization of Original Samples

Original samples with different magnitudes need the processing of standardization. Equation (1) is employed to standardize original samples and transform the figures of each indicator into 0.1~0.9, shown in Tab.Ⅲ. The standardized samples retain characteristics of original samples and have a better comparability.

$$Y = 0.1 + 0.8 \times (X - X_{\min}) / (X_{\max} - X_{\min}) \tag{1}$$

In (1): Y is standardized value, X is actual value, $X_{\max}$ and $X_{\min}$ are the maximum and minimum of original samples for an indicator.

TABLE III. STANDARDIZED SAMPLES

Year	Standardized Samples of Indicators						
	W1	W2	W3	W4	W5	W6	A
1993	0.1	0.1	0.1	0.1	0.1	0.1	0.1
1994	0.195	0.162	0.135	0.158	0.393	0.347	0.115
1995	0.287	0.220	0.175	0.194	0.639	0.592	0.143
1996	0.360	0.304	0.204	0.224	0.789	0.664	0.166
1997	0.412	0.387	0.245	0.252	0.847	0.689	0.204
1998	0.442	0.465	0.299	0.300	0.836	0.607	0.235
1999	0.471	0.537	0.373	0.382	0.811	0.546	0.293
2000	0.529	0.603	0.424	0.444	0.825	0.638	0.342
2001	0.590	0.693	0.724	0.531	0.839	0.63	0.425
2002	0.652	0.761	0.793	0.680	0.82	0.590	0.547
2003	0.748	0.827	0.838	0.794	0.837	0.679	0.723
2004	0.9	0.9	0.9	0.9	0.9	0.9	0.9

III. BP NEURAL NETWORK MODEL

When indicators and samples are fixed, BP neural network could be modeled and trained. To test whether the trained network gives reasonable response to outside input, a generalization test follows.

A. Modeling

1) Structure

Theory and practice have proved that three-layer BP neural network model is sufficient to simulate the complex nonlinear relationship between input and output. More layers may improve the ability of ANN to simulate more complex problems, but it may occupy much more computer resources at the same time.

This study utilizes a three-layer BP neural network model and the GUI solution of Matlab.

2) Hidden nodes

The number of neurons in the output layer and input layer has been identified by the study itself in a three-layer BP neural network. However, there is no theoretical guidance to determine the number of hidden nodes at present. Too few nodes can not provide good fault-tolerance and too many nodes may delay the study time. Some papers recommend that the number of neurons in middle layer can be more than half of the total number of input and output neurons or be the sum of them. Then, we may adjust the number in accordance with the actual situation. To reduce the workload, number of neurons should be as few as possible.

The number of hidden nodes is choosing to be six after several adjustments.

3) Response function

In practical application, the appropriate response function can be selected according to requirement and sigmoid functions are usually used.

Referring to the modeling experience, tansig function is used in hidden layer and purelin function is used in output layer.

Therefore, the topology structure of this BP neural network is 6-6-1, shown in Fig. 1.

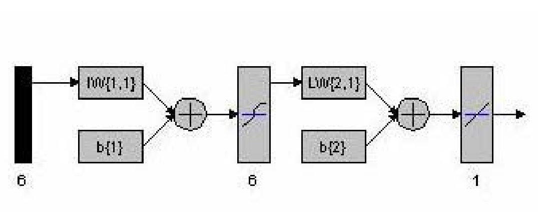

Figure 1. Topology structure of network

B. Training

Standardized samples of W1~W6 are used as input data and samples of A as output data. Goal is 0.00001. Largest epochs are 1000. The remaining options use default values. Start training with TRAINLM. As shown in Fig. 2, training reaches its goal just after eight epochs.

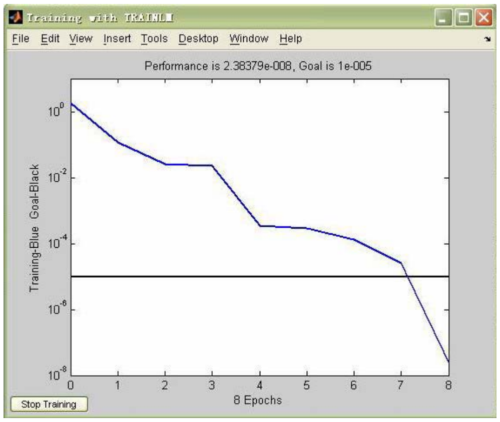

Figure 2. Training with TRAINLM

Comparing samples of A with training outputs, we may confirm whether the network is fitting to actuality. As shown in Fig. 3, the model gives a good fit.

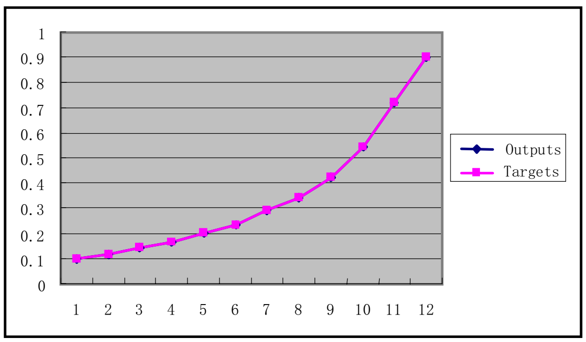

Figure 3. Network fitting test

C. *Generalization Test*

The capability that network model can give reasonable response to outside input is called as generalization. Now we will test the generalization of the trained network.

The average of the figures of two adjacent years which form a matrix (11×6) is used as input data and output data to test the BP neural network model.

After testing, the absolute deviation of simulate value and actual value are below 0.05. As shown in Fig. 4, the model performs well.

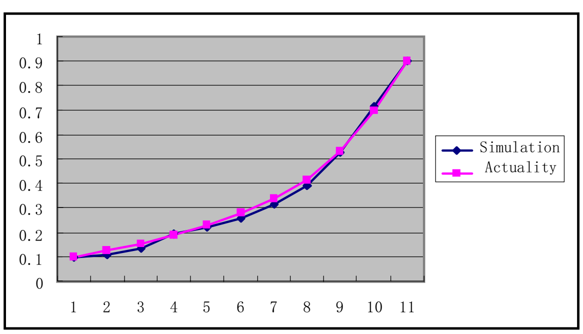

Figure 4. Generalization test

IV. SENSITIVITY ANALYSIS

Sensitivity analysis of the six selected indicators will be done to make a study about their impacts on the development of private passenger cars based on the BP neural network model.

A. *Sensitivity Coefficients*

When the value of an independent variable is reduced or increased, the differential coefficient of the dependent variable is the sensitivity coefficient of this independent variable, as in

$$S_i = \frac{dv}{dp_i} \quad (2)$$

In (2): S_i is the sensitivity coefficient of independent variable i, v is the value of dependent variable, p_i is the value of independent variable i.

The figures of 2001~2004 which form a matrix (4×6) are increased by 10%. The new matrix is used as input matrix. Then, we obtain the simulating output. Use (2) to calculate the sensitivity coefficients of the six indicators in the four years, shown in Tab.Ⅳ.

TABLE IV. SENSITIVITY COEFFICIENTS OF SIX INDICATORS

Year	Sensitivity Coefficients of Indicators					
	W1	W2	W3	W4	W5	W6
2004	0.497	0.844	1.494	0.412	-0.028	-0.644
2003	0.354	0.911	0.999	0.465	-0.053	0.050
2002	0.230	0.719	0.646	0.368	-0.074	0.234
2001	0.085	0.613	0.271	0.336	-0.273	0.202

B. *Sensitivity Analysis*

According to the Sensitivity coefficients of the four years calculated above, the six indicators can be divided into two types.

1) Except fuel price, the sensitivity coefficients of other indicators change smoothly.

In the four years, with the exception of fuel prices (Fuel price is close related to the Purchasing Price Indices of Fuel and Power, so the study use the former instead of the later), the symbol of sensitivity coefficient of other indicators did not change, shown in Fig.5.

This phenomenon means these indicators have fixed positive or negative effects on the development of private passenger cars. The sensitivity coefficients of gross domestic product, total number of employed persons, length of highways and annual per capita disposable income index of urban residents are plus. It suggests that these indicators have positive effect on the development of private passenger cars.

The sensitivity coefficients of consumer price index of urban area are minus. It shows that the consumer price index of urban area have a negative effect on the development of private passenger cars.

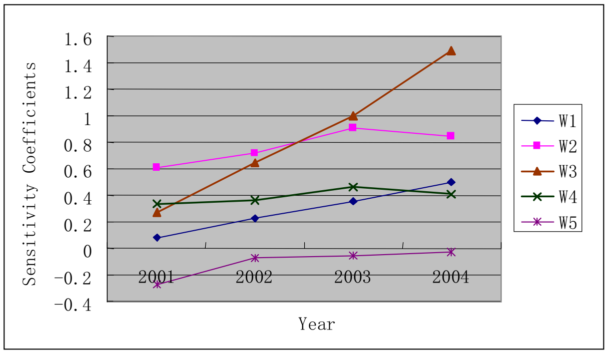

Figure 5. Sensitivity coefficients of W1~W5

We should pay more attention to the sensitivity coefficients of length of highways for its notable upward trend in recent years. It indicates that the development of transportation infrastructure is one of the strong forces to the development of private passenger cars.

2) The sensitivity coefficients of fuel price change suddenly.

The sensitivity coefficients of fuel price are plus between 2001 and 2003. It begins to decrease after 2002 and changes into minus in 2004, shown in Fig. 6.

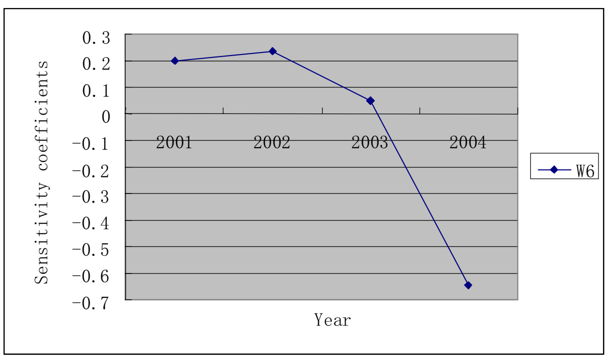

Figure 6. Sensitivity coefficients of fuel price

This phenomena show that the impact of higher fuel prices on private passenger cars is not obvious in the first year. Under the effects of other factors, the quantity of private passenger cars keeps a rising trend. However, the rising trend has gradually weakened. In 2004, the ever-rising fuel price may go beyond consumers' receptivity. The sensitivity coefficients of fuel price become minus. The development of private passenger cars is seriously hampered by high fuel price. It tallies with the current situation of the private passenger cars' market.

V. CONCLUSIONS

This study employs BP neural network to simulate the development of Chinese private passenger cars. The model avoids the limits of traditional method when describing a complex and nonlinear problems and gives a good fit.

Sensitivity analysis of various indicators is done based on BP neural network. We obtain some reasonable conclusions and mainly explain that the negative impact of high fuel price upon private passenger cars is more and more apparent.

Because of the inherent shortcomings of BP neural network, it is somewhat subjective when choosing data and the structure of network. We may study in depth about how to avoid the error of subjective choices, and reflect the characteristics of the development of Chinese private passenger cars fully and objectively.

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